NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

IMPROVING AIRCRAFT REFUELING PROCEDURES AT NAVAL AIR STATION OCEANA

by

Matthew T. Geiser

June 2012

Thesis Advisor:	Harrison Schramm
Second Reader:	Gerald Brown

Approved for public release; distribution is unlimited

THIS PAGE INTENTIONALLY LEFT BLANK

REPORT DOCUMENTATION PAGE				*Form Approved OMB No. 0704-0188*
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington DC 20503.				
1. AGENCY USE ONLY *(Leave blank)*	**2. REPORT DATE** June 2012		**3. REPORT TYPE AND DATES COVERED** Master's Thesis	
4. TITLE AND SUBTITLE Improving Aircraft Refueling Procedures at Naval Air Station Oceana			**5. FUNDING NUMBERS**	
6. AUTHOR(S) Matthew T. Geiser				
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000			**8. PERFORMING ORGANIZATION REPORT NUMBER**	
9. SPONSORING /MONITORING AGENCY NAME(S) AND ADDRESS(ES) N/A			**10. SPONSORING/MONITORING AGENCY REPORT NUMBER**	
11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government. IRB Protocol number ______N/A______.				
12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release; distribution is unlimited			**12b. DISTRIBUTION CODE** A	

13. ABSTRACT (maximum 200 words)

This thesis seeks to improve aircraft refueling at Naval Air Station (NAS) Oceana, VA, using aircraft waiting time for fuel as a measure of performance. We develop a computer-assisted discrete-event simulation to model refueling at NAS Oceana using airfield data from October 2011. Our study focuses on six factors: the total number of mobile refueling trucks, the rate of fuel flow from each truck, the quality of information sharing, the percentage of aircraft that refuel using hot pits (high-speed, in-ground refueling stations), and the normal operating band (both the upper limit and the lower limit) of jet fuel level that each truck driver maintains. We use experimental design and determine the efficiency of various decisions for reducing fuel wait time. We conclude with specific recommendations for NAS Oceana leadership.

14. SUBJECT TERMS Simulation, Queueing, Aircraft Fuel			**15. NUMBER OF PAGES** 65
			16. PRICE CODE
17. SECURITY CLASSIFICATION OF REPORT Unclassified	**18. SECURITY CLASSIFICATION OF THIS PAGE** Unclassified	**19. SECURITY CLASSIFICATION OF ABSTRACT** Unclassified	**20. LIMITATION OF ABSTRACT** UU

NSN 7540-01-280-5500 Standard Form 298 (Rev. 2-89) Prescribed by ANSI Std. 239-18

THIS PAGE INTENTIONALLY LEFT BLANK

Approved for public release; distribution is unlimited

IMPROVING AIRCRAFT REFUELING PROCEDURES AT NAVAL AIR STATION OCEANA

Matthew T. Geiser
Lieutenant Commander, Supply Corps, United States Navy
B.S., The Ohio State University, 1994

Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

from the

NAVAL POSTGRADUATE SCHOOL
June 2012

Author: Matthew T. Geiser

Approved by: Harrison Schram
Thesis Advisor

Gerald Brown
Second Reader

Robert Dell
Chair, Department of Operations Research

THIS PAGE INTENTIONALLY LEFT BLANK

ABSTRACT

This thesis seeks to improve aircraft refueling at Naval Air Station (NAS) Oceana, VA, using aircraft waiting time for fuel as a measure of performance. We develop a computer-assisted discrete-event simulation to model refueling at NAS Oceana using airfield data from October 2011. Our study focuses on six factors: the total number of mobile refueling trucks, the rate of fuel flow from each truck, the quality of information sharing, the percentage of aircraft that refuel using hot pits (high-speed, in-ground refueling stations), and the normal operating band (both the upper limit and the lower limit) of jet fuel level that each truck driver maintains. We use experimental design and determine the efficiency of various decisions for reducing fuel wait time. We conclude with specific recommendations for NAS Oceana leadership.

THIS PAGE INTENTIONALLY LEFT BLANK

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF ACRONYMS AND ABBREVIATIONS

AICc	Akaike information criterion corrected
AM	Ante meridiem
DES	Discrete-event simulation
C-17	Strategic and/or tactical transport aircraft (operated by U.S. Air Force)
C-5	Strategic transport aircraft (operated by U.S. Air Force)
cdf	Cumulative distribution function
E-6B	Airborne command-post aircraft (operated by U.S. Navy)
F/A-18	Fighter and/or attack aircraft (operated by U.S. Navy and Marine Corps)
FRS	Fleet Replacement Squadron
G/G/s	Multi-server queue, with general interarrival and service time distributions
gpm	Gallons per minute
JDK	Java development kit
M/M/1	Single-server queue, with Markovian interarrival and service time distributions
M/M/k	Multi-server queue, with Markovian interarrival and service time distributions
NAS	Naval Air Station
NASA	National Aeronautics and Space Administration
NAVSUP	Naval Supply Systems Command
NIST	National Institute of Standards and Technology
NOLH	Nearly orthogonal Latin hypercube
pdf	Probability density function
PM	Post meridiem
VFA-106	Strike Fighter Squadron 106

THIS PAGE INTENTIONALLY LEFT BLANK

EXECUTIVE SUMMARY

Naval Air Station (NAS) Oceana, VA, is the U.S. Navy's East Coast master jet base. It is comparable both in size and activity to many large civil airfields in that it operates and services a large number of jet aircraft daily. Unlike civil airfields, it experiences large fluctuations in volume and type of air traffic throughout any given day. One key support activity for aircraft is fueling.

Jets cannot fly without fuel. If the capacity of a refueling system is adequate and customer demands are regular, as is the case at most civil airfields, waiting times are minimized. But as demands become increasingly irregular, periodic surges may overwhelm the capacity of the system and lead to longer wait times for refueling. This is currently the case at Oceana.

Fuel operations at Oceana are a complex interaction between multiple customer aircraft with varying fuel requirements and limited numbers of mobile refueling trucks, eighteen high-speed in-ground refueling stations (also known as 'hot pits'), and three truck refilling stations.

To gain understanding of causes and potential mitigations of fuel delays, we develop a computer simulation model to analyze refueling at NAS Oceana using airfield data from October, 2011. Based on our modeling, we recommend the following actions to minimize waiting times:

1) Ensure each mobile refueling truck and each driver is equipped to consistently and safely deliver jet fuel near the practicable limit of 150 gallons per minute (gpm). This action should require minimal additional cost.

2) Require that an aircrew member or maintenance personnel provide a reliable estimate for the amount of fuel required to the truck dispatcher with adequate lead time, so that each fuel truck driver can anticipate requirements. This action also should not require additional cost.

3) Re-evaluate the current hot pit policy, which limits total hot pit refueling to 20% or less of all refuelings. Previous analyses considered the costs of fuel burned in the hot pits, but did not consider the potential time savings. We demonstrate that increasing hot pit usage by 7% will be operationally equivalent to adding another truck.

ACKNOWLEDGMENTS

At one time acknowledgments were far fewer and compressed into the abstract section of theses at the Naval Postgraduate School. Just as our theses seem to have lengthened during the information age (acknowledging that we also stand on the shoulders of giants), we now find more space to thank people, places and things. My intent is to acknowledge everybody, hoping that I miss no one.

First and foremost, to my wife, Erika, and to our daughter, Emily: I look forward to our time together after this experience. Thank you for helping me to make it through.

To my parents, my brothers, my sister, and my grandparents, thank you for giving me a solid foundation with lightness.

To my thesis advisor, CDR Harrison Schramm, thank you for the time, patience, and deft guidance that you provided throughout this process. *Divine Comedy* comes to mind. Though it was 712 years ago (nearly to the day!) when Dante himself passed through those famous gates, our simulation could run that in a little over 11 hours. I am much wiser for the experience.

To my second reader, Dr. Jerry Brown, thank you for your time, for you keen insights, for your encouraging words, and for your practical guidance on how to clearly and naturally write about Operations Research. I should have followed it much earlier.

To CDR Trent Kalp, LT Jeff Knight, and Mr. Pat O'Donnell, thank you for answering my endless questions about the fuels operation at NAS Oceana. I can now say that I know a little more than simply "purple pipes mean jet fuel". LCDR Tom Decker, Master Chief Richard Mooney, and Jim "Gramps" McDowell also provided key support.

To Dr. Arnie Buss, thank you for enthusiastically supporting this work and for providing invaluable assistance and expertise when most needed. I appreciate the help you have given me throughout my time at the Naval Postgraduate School.

To Dr. Keebom Kang, thank you for getting me started on the problem and for your superb course in Logistics Engineering.

To my nephew, Eric Hill, thank you for patiently helping me sift through lines and lines of computer code in search of errors. You are a part of this work as well.

To George Rhoads, whose sculpture, *Untitled (Aquarium)*, serves as a playful example of queueing and randomness. One can view this at the Community Hospital of the Monterey Peninsula, located on the main floor directly above the Emergency Room.

In no particular order, I would also like to thank the following people for providing assistance, ideas, and inspiration: Dr. Mike Atkinson, Dr. Ned Dimitrov, Dr. Paul Sanchez, Dr. Susan Sanchez, Dr. Eva Regnier, Dr. Rob Dell, COL (Ret) Jeff Appleget, CDR Dick McGrath, CDR Mike Bissell, CDR Walt DeGrange, LTC Rob Shearer, LCDR Phil Mock, 1TEN Sofia Miranda, LT Don Roberts, and CPT Mario Solano.

I would like to acknowledge those men and women who perform maintenance and sustainment work each day. You won't always be thanked for your efforts, but you almost certainly will hear when additional support is needed. You continue to be my personal heroes.

Last but not least, to our dog, Puppy. Although you probably won't read this, we couldn't ask for a better family companion. We look forward to the reunion when we return from overseas.

As Box and Draper (1987) point out on page 424 of *Empirical Model-Building and Response Surfaces*, I hope that this model is useful.

I. INTRODUCTION

> Naval aviation is a warfighting force that is an integral part of the ability of the Navy, Marine Corps, and joint forces to deter or win regional conflicts and major power wars. (Naval Aviation Enterprise, 2012)

> Naval aviation is critical to an evolving military shaped by war and fiscal pressures. (Naval Aviation Enterprise, 2012)

A. NAVAL AVIATION

Naval aviation includes air elements of both the U.S. Navy and the U.S. Marine Corps. As described in the most recent long-term guidance from Commander, Naval Air Forces (Naval Aviation Enterprise, 2012) a primary function is to meet international responsibilities and national imperatives, in part using manned, tactical fighter and/or attack aircraft. Naval aviation platforms may broadly be described as rotary-wing, maritime patrol, strike, and unmanned. Together, these platforms form a massive enterprise funded with more than $40B annually (Department of the Navy, 2012) and encompassing over 190,000 Marines Corps, Navy, civilian, and contractor personnel. (Naval Aviation Enterprise, 2011)

We consider improving the operation of a small piece of this enterprise; fueling operations for aircraft at Naval Air Station (NAS) Oceana. Specifically, we consider fourth-generation F/A-18E/F Super Hornets and legacy F/A-18A/B/C/D Hornets, along with their operators, maintainers, and support personnel. Efficient daily operations, in terms of both money and time, are required to maintain combat readiness.

B. NAVAL AIR STATION, OCEANA

Naval Air Station (NAS) Oceana, located in Virginia Beach, Virginia, is the Navy's "East Coast master jet base" and is one of the world's busiest airfields, with varying levels of flight activity that peak at more than 200 sorties per day and more than 40 aircraft takeoffs and landings per hour, based on NAS Oceana Air Operations Department data for October 2011 (Decker, 2011).

Oceana is home to 16 deployable fleet squadrons and three shore squadrons, including Strike Fighter Squadron 106 (VFA-106), the largest Fleet Replacement Squadron (FRS) in the Navy. The mission of VFA-106 is to provide combat ready F/A-18A-F aircrew for the fleet, the Marine Corps operating forces and F/A-18A-F support squadrons. (Strike Fighter Squadron One Zero Six, 2012)

The FRS provides both initial and refresher training for Hornet and Super Hornet pilots before they join deployable fleet squadrons. The FRS also evaluates the operational and training effectiveness of the fleet squadrons in some contexts. All told, the FRS and the fleet squadrons maintain, service, and fly a total of 130 Hornets and 170 Super Hornets. The total complement of tactical fighter and/or attack aircraft at NAS Oceana represents 25% of the tactical aircraft required by the Navy and Marine Corps. (Government Accountability Office, 2010)

Additionally the base services approximately 3,500 transient aircraft (that do not consider this home) each year. These arrivals vary greatly in type and number, ranging from small local helicopters to large Air Force cargo aircraft.

C. NAS OCEANA SUPPORT OPERATIONS

Not only are Oceana's runways busy, the support operation is also busy. The rate of consumption of jet fuel averages 115,000 gallons per day (NAVSUP Fleet Logistics Center, Norfolk, 2012) and sometimes exceeds 300,000 gallons per day, based on NAS Oceana Fuels Division monthly fuel reporting from October 2011 (Knight, 2011). Military aircraft operations are driven by training and readiness requirements, to include factors such as range availability, lunar cycle, weather, and, in the case of naval aviation, ships' schedules. This is fundamentally different than commercial operations, where flight schedules are optimized to maximize profit given some reasonably predictable demand.

NAS Oceana Fuels Division supports on average 120 aircraft refueling events per day. These tend to compress into several peak periods with slower intermediate periods and less activity overnight.

D. NAS OCEANA FUEL DEMAND PROFILE

While all squadrons are required to publish a daily flight schedule (Office of the Chief of Naval Operations, 2009), factors such as weather, shifting operational requirements and aircraft availability may lead to sudden deviations from this plan. As aircraft come and go, the fuel required by aircraft leads to second-order effects on the fuel delivery system. The net result is a refueling system wherein the aircraft arrival times (and, subsequently, fuel demands) are sometimes known, but frequently change. When arrival times are known, the amount of fuel required by each aircraft is typically not known by the support personnel prior to refueling the aircraft. Due to these complicating factors, refueling tends to require variable waiting times that depend on the number of and size of fuel demands, discovered in real-time with minimal advanced warning.

E. PROBLEM STATEMENT

The goal of this thesis is to identify, analyze and propose a portfolio of solutions to refueling delays at NAS Oceana. Broadly, we explore the following actions:

1. Policy changes – zero-cost (or near zero-cost) measures that increase efficiency by changing the rules under which the system operates. Examples of policy changes may be shifting takeoff times for jets (i.e. staggering scheduled times instead of having ‘waves’ of aircraft departing and arriving), as well as reexamining policies on ‘hot pit’ utilization.

2. Materiel recommendations – increase efficiency by adding or changing resources, such as fueling trucks or manpower. One example of a materiel recommendation might be to forego acquiring additional trucks beyond a point of diminishing returns. If system performance levels off due to diminishing returns on the number of operating trucks, greater focus on the ideal employment of limited personnel to maximize actual fuel flow rate could produce results on par with making additional fuel-ferrying trips.

F. BENEFITS OF THE STUDY

Using computer simulation, this research provides a tool to explore acquisition and policy changes for the Regional Supply Officer at NAS Oceana with the goal of reducing wait times for refueling and thereby increase operational availability of all customer aircraft. This information can be used to present objective data to other decision-makers within the naval aviation community in order to efficiently use all refueling assets to maximum effect.

II. SIMULATION

We use discrete-event simulation to identify tensions and explore tradeoffs between various options open to the airfield managers on fueling performance as measured by minimizing mean customer aircraft wait times. These options may include physical changes, such as acquiring more fuel trucks, or policy changes, such as coordinated scheduling and sharing of information.

Computer simulation allows us to explore the behavior of a system under various scenarios for problems that are intractable for a closed-form solution. We use the uncertainty of a pseudo-random number generator as a proxy for real-world randomness. Understanding variability is a key to understanding the dynamics of a system's behavior.

A. LITERATURE REVIEW

1. Neighboring Studies of Airlines

Stroup and Wollmer (1992) propose a network model to control fuel use by the commercial airline industry, by minimizing the total cost of fuel for individual flights with multiple stops. Abdelghanya et al. (2004 and 2005) propose a shortest-path algorithm to project flight delays and/or a mathematical programming formulation to optimize tradeoffs of different aviation fuel positioning and loading strategies in terms of fuel costs and maintenance costs. None of these approaches applies to our problem, because commercial interests focus exclusively on finding the optimal solution to minimize dollar costs for a network of static aircraft routes; whereas the military seeks to minimize the average time that aircraft wait for fuel, with less predictable system behavior.

2. Related Studies

Airport modelers (Pitfield, Brooke, & Jerrard, 1998, and Pitfield & Jerrard, 1999) propose Monte Carlo simulation of ground operations to analyze the interaction between facility layout and aircraft arrivals and departures with the objective of streamlining runway operations. While these studies do not involve aircraft refueling, they do

combine probabilities with traffic patterns to run simulations that give insight to airport operations. Queueing has been used in other studies involving naval aviation. Dummar (2011) proposes a computer simulation model for studying the training cycle of Marine Corps pilots. A key feature of this model is that it attempts to simulate the congestion of student pilots within a constrained training pipeline. Similarly, we intend to model aircraft and refueling truck queueing behavior through computer simulation.

The Aviation Systems Division at NASA Ames Research Center conducts research on air traffic management, including *surface traffic management* (NASA, 2011). Quinn and Zelenka (1998, p. 7) conclude that "resources could be managed more effectively if ramp management personnel had more detailed, up-to-date schedule information". Greater collaboration on airline ramp operations includes greater situational awareness for refueling truck drivers. This applies to both military and civilian airfields. Behavior of ground delays in high traffic scenarios at Dallas/Fort Worth International Airport is analyzed by Jung et al. (2011), with the objective of creating a decision support tool to coordinate ground controllers and tower controllers, thereby relieving airfield congestion with the added goal of reducing fuel consumption. Refueling never enters this analysis, making it fundamentally different than Oceana's problem.

Surprisingly, the health care industry contains ample cases relevant to our analysis, where computer simulation is used to model customer wait times. Several authors (Jun, Jacobson, & Swisher (1999), Jacobson, Hall, & Swisher (2006), and Mustafee, Katsaliaki, & Taylor (2010)) periodically outline a comprehensive taxonomy of papers that demonstrate the growing trend in the use of computer simulation to model complex queueing behavior. A notable example among the references cited is work by Kumar and Kapur (1989) that describes the application of a simulation model to inform the scheduling of Emergency Room staff at Georgetown University Hospital. We assert that NAS Oceana functions like a hospital for landing aircraft that need to be serviced, and refueling trucks function as the hospital staff faced with managing multiple tasks. Unique differences in our problem that we address later in this chapter include the customer arrival pattern, service time variability, and the existence of a secondary queue.

3. Computer Simulation Software Options

Swain (2011) identifies 15 simulation platforms suitable for our analysis.

Currently two computer simulation options are discrete-event simulation (DES) and discrete-time simulation. Of particular interest to us is that DES, especially when studying the complex interactions within a system of many components, tends to have fewer errors because it avoids 'tie breaking', whereas multiple events may occur within the same time-interval in a discrete-time simulation. (Buss and Halwachs, 1999) DES avoids the problem by handling events sequentially, by their scheduled time. This also allows transitions to be dictated by the underlying (possibly random) process, instead of coercing events into fixed time steps.

For the remainder of this thesis, when we refer to 'simulation', we specifically mean DES. A DES model may be described with four basic elements (Schruben, 1987): parameters, state variables, events that are connected via an event graph, and a set of scheduling relationships or rules between events. Parameters are characteristics of a system that are specified by the modeler and that do not change during a simulation instance. State variables are measurable components of a system that may change over time. An event graph is a schematic representation of simulation scheduling relationships, using nodes and directed edges. (Sargent, 1988)

B. FUELING

The delivery of jet fuel from the central depot to customer aircraft at NAS Oceana consists of three interrelated processes: cold fueling, hot fueling, and refilling of fuel trucks.

1. 'Cold' Aircraft Refueling Using Fuel Trucks

Fuel is primarily delivered to aircraft that are parked in refueling areas using mobile refueling trucks that transport fuel to the location of each stationary aircraft (henceforth referred to as 'cold refueling'). Tenant aircraft squadrons have separate designated refueling areas from transient aircraft that are not affiliated with NAS Oceana.

During cold refueling a truck with finite capacity delivers a knowable (but not necessarily known) quantity of fuel to an aircraft with engines shut down.

The presumed advantage of cold refueling is that no fuel is expended by aircraft engine idle operation during the refueling operation. We say ‘presumed advantage’ because the analysis leading to that conclusion accounts for the monetary costs of fuel burned at ground idle, or approximately five gallons per minute (gpm), but does not account for the opportunity costs associated with aircraft waiting.

The disadvantages of cold fueling are two-fold. First, the truck spends transit time as it ferries fuel from refilling station to awaiting aircraft. When the truck runs out of fuel it must return to a refilling station to replenish. Secondly, the aircraft goes through full engine shutdown and engine start checks before it may be flown again. We introduce these difficulties to illustrate that neither hot nor cold fueling is a clearly dominating strategy for airfield operations.

2. 'Hot' Aircraft Refueling Using Flight Line Refueling (or ‘Hot Pits’)

Fuel may also be transferred to aircraft using fixed high-speed fueling hydrants known as ‘hot pits’ (henceforth referred to as ‘hot refueling’) that directly connect to the in-ground fuel system. Because the in-ground fuel system feeds directly from the airfield storage tanks, the hot pit capacity is the airfield capacity which exceeds any individual day’s demands by a wide margin and will henceforth be assumed infinite in our analysis. In contrast to cold refueling, an aircraft is ground taxied to the stationary delivery sites and fuel is transferred while the aircraft is operating at ground-idle power.

A few potential advantages of this refueling method are that aircraft do not need to be restarted, fuel is handled only once (saving labor and time), and fuel can be delivered at a faster rate than a fuel truck can provide due to system pressure. Disadvantages of this method are that fuel is consumed at an estimated rate of five gallons per minute while the aircraft idles, a pilot must be present inside the aircraft, and the physical configuration of some aircraft preclude them from using a hot pit.

NAS Oceana has had a policy emphasizing the use of cold refueling over hot refueling since approximately April 2006. Airfield regulations, in the form of standard operating procedure at NAS Oceana, restrict hot refueling to 20% or less of the total number of refueling events. We explore the relative merits of cold and hot fueling with customer time as our single metric. While there is no service-approved metric for the cost associated with waiting for fuel, stakeholders at NAS Oceana (i.e. Regional Supply Officer, airport manager, and squadron personnel) agree that avoidable delays in fueling are detrimental to flight operations. Their concern is simple—aircraft that are waiting for fuel are unavailable to fly.

We sidestep the issue of estimating costs by presenting our results in terms of the marginal increase in aircraft events per day. Ultimately, the decision as to what is 'cost effective' for training will lie with the leadership at Strike Fighter Wing Atlantic. With this in mind, we explore no-cost, low-cost and moderate cost alternatives to the current system. We note that understanding the cost of aircraft downtime is an open area for research.

Ultimately, tradeoffs between fuel dollar costs and other costs are beyond the scope of our analysis and will have to be evaluated by decision makers using multiple criteria.

For the remainder of this thesis, the act of providing an aircraft with jet fuel without regard to method (i.e. hot or cold) will be referred to as 'fueling'.

3. Fuel Truck Replenishment

Mobile refueling trucks have fixed capacity and therefore also must replenish (a term henceforth referred to as 'refilling'). Truck refilling always occurs at a single location with three service stands and the decision to refill is currently at the discretion of the individual fuel truck driver. Current practice is that a driver does not partially refuel an aircraft, because squadrons prefer to get an aircraft refueled in a single visit by one fuel truck rather than multiple visits. Drivers typically decide when to refill in order to maintain sufficient fuel onboard, based on fuel state and existing operating tempo at the field.

This situation is a complex, multi-stage queueing problem and does not, to our knowledge, have a tractable closed-form solution. Among the complexities are that Markovian aircraft arrivals and service times would be very poor assumptions. Pilots generally know when they are going to land before they take off, and the amount of time an aircraft has been flying offers a lot of information about how much longer it will fly. Known departure times are strongly correlated with return times. Return times are, in turn, strongly correlated with fueling requirements.

Both refueling trucks and hot pits behave as servers for aircraft (the primary customers) in the first stage; an analytic challenge of this problem is that some of the servers (specifically all of the mobile refueling trucks) *themselves act as customers* in the second stage. Following the taxonomy of Ross (2010) the second stage of the model is a 'closed system', where refueling trucks behave as customers when coming out of service to take on more jet fuel for delivery to aircraft.

C. DATA

Our aircraft demand data comes from the Fuels Division Officer (for overall fuel data), the airport manager (for transient aircraft data), and their respective staffs. We use the data from the Fuels Division Officer's Monthly Fuel Issues Report for October 2011 (J. Knight, personal communication, November 14, 2011; see Appendix A for a sample) and recreate aircraft arrivals and refueling requirements for our simulation. This forms the core of our model, around which we build using additional information such as fuel flow rates, truck transit times based on geography, and anticipated transition periods.

A key difficulty for operators is the interaction between customer aircraft, hot pits, mobile refueling trucks, and truck refill stations. We present a representative sample of three consecutive days of observed behavior (Figures 1, 2, and 3). In the first case there is a large spike in aircraft arrivals between 2:00 PM and 4:00 PM.

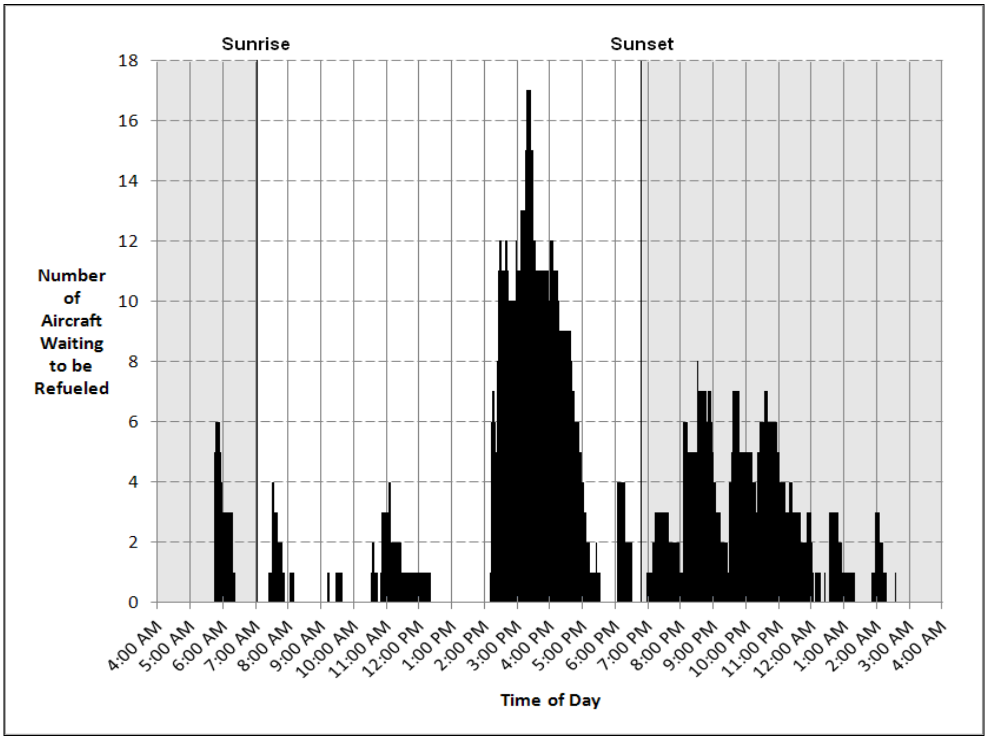


Figure 1. Refueling queue length as a function of time of day for 03 October 2011. Note that the queue is empty in the overnight hours with peaks in mid-afternoon to early evening. These peaks coincide with returning morning flights and preparation for evening flights.

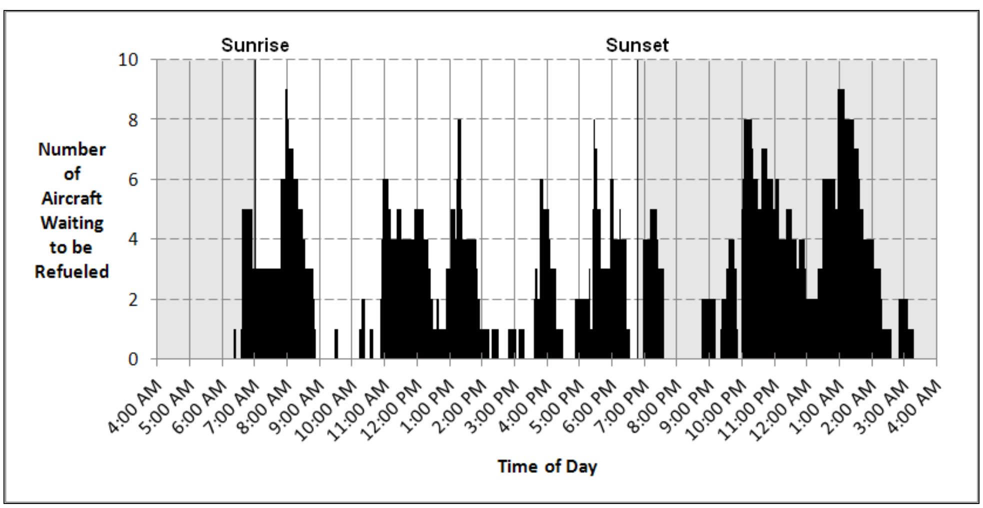


Figure 2. Refueling queue length as a function of time of day for 04 October 2011. Note that there is far less peaking in the mid-afternoon to early evening hours compared to the previous day.

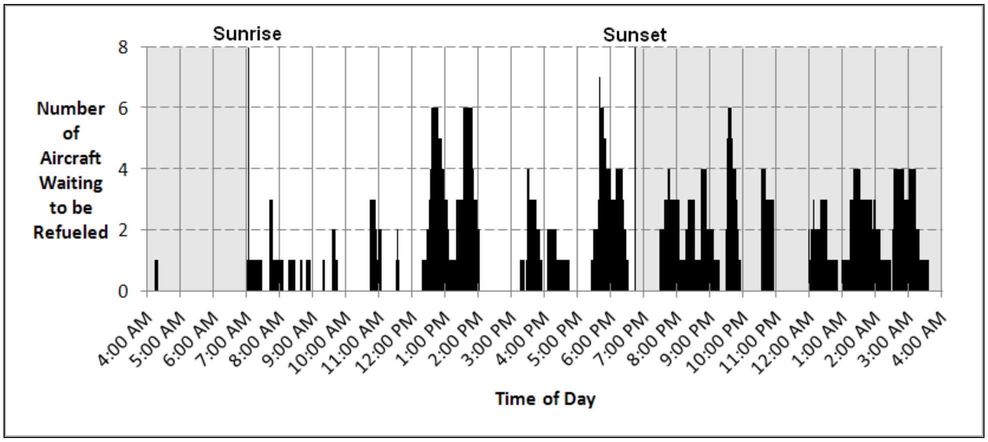


Figure 3. Refueling queue length as a function of time of day for 05 October 2011. Note that there is significantly less refueling activity compared to the previous two days. The peak near 1:00 PM corresponds to morning flights returning to launch again as afternoon missions; the peak near 6:00 PM corresponds to sunset (6:43 PM), when aircraft are launching for night training missions (Time and Date AS, 2012).

D. MATHEMATICAL MODELING

Our simulation model is a two-stage, multiple-server queue. Following Ross, the first stage is an 'open system' in which aircraft are modeled as customers in a G/G/s queue with two server types (trucks and “hot pits”). Aircraft (customers) join the system when they enter to refuel, either upon landing or by request from squadron maintenance control, and leave the system when they are fueled, either by a mobile refueling truck or at a hot pit.

1. Modeling Assumptions

In this section, we make our modeling assumptions explicit. First, based on data for October 2011, we observe an empty queue at 4:00 AM daily. We therefore are able to treat each day as a separate process, with 4:00 AM acting as the starting time and ending time each day for our simulation runs. This is important to our study because we are interested in the system’s daily behavior, commencing an epoch at a moment when the aircraft refueling queue is completely empty. We do not need to have a “run-in period” for the simulation (Pidd, 1994, p. 12), and our explicit assumption is that the

queue will be empty at the same time each day, allowing us to treat each day separately. We do not assume that this time is static, as it may have time-of-year effects (i.e. earlier in the winter, later in the summer). Secondly, we have removed degrees of freedom by using fixed, deterministic times to represent some delays, specifically:

- the transit time it takes for each dispatched refueling truck to reach a customer aircraft,
- the transit time it takes for each truck to reach the refilling stations,
- the time it takes to couple a refueling truck with a customer aircraft, and
- the time it takes for a jet to reach a hot pit.

Given NAS Oceana configuration and weighing speed restrictions for vehicles near aircraft operations, we assume that each dispatched refueling truck takes ten minutes to reposition to a new customer, five minutes to reach the refilling stations, and three minutes to commence refueling after arriving to service an aircraft. Additionally, we assume that it takes the same amount of time for a jet to reach a hot pit as it does for a truck to reach a jet.

When verifying our model against theoretical results, we assume an infinite population of customer aircraft. We defend this assumption by noting the large number of aircraft (in excess of 250) that are available for use at NAS Oceana compared to the maximum number of aircraft (typically fewer than 20) that wait for fuel at any given time. In other words, the operating pool of aircraft that may be flown is sufficiently large for us to be unconcerned about how the current state of any particular aircraft affects the distribution of service arrivals and fuel requirements.

In contrast to the first stage, an infinite population assumption is not warranted for trucks being refilled, as the number of trucks waiting affects the distribution of arriving trucks.

2. The Model

For our simulation, we treat the following items as adjustable parameters: the percentage of aircraft that use hot pits, the total number of mobile refueling trucks

available within the system, the operating band of jet fuel level that each truck driver maintains, the actual fuel delivery rate from each truck, and whether or not the amount of fuel required by each aircraft is known in advance.

E. SPECIFICS OF OUR MODEL

1. Parameters

Table 1 presents our model's six adjustable parameters. These features map to actions that the airfield manager could take, and thereby inform his decisions.

Adjustable Parameter Description	Variable Type	Units
Total number of mobile refueling trucks available	integer	trucks
Effective flow rate during cold refueling from refueling trucks	continuous	gpm
Minimum fuel level at which refueling truck drivers decide to refill	continuous	gallons
Maximum fuel level that trucks carry	continuous	gallons
Percentage of aircraft that conduct refueling at hot pits	percentage	numeric
Whether or not truck drivers are aware of actual fuel required before attempting to refuel jets, which we call "value of information"	binary	numeric

Table 1. Summary of parameters we use for our DES model. For example, 'Total number of mobile refueling trucks available' consists of integer values that specify how many trucks exist within the model during each unique run. Together these adjustable parameters form the design points for our analysis and represent deliberate actions that the airfield manager could take.

2. Fixed Parameters

Table 2 presents our model's fixed parameters, or those features we consider as stationary for the entire duration of our study (i.e. unchanged across all cases). These could be adjusted, but do not inform our current effort.

Fixed Parameter Description	Value	Unit
Total number of truck refilling stations	3	refill stations
Rate of jet fuel flow from truck refilling stations	+170	gpm
Total number of hot pits	18	hot pits
Rate of jet fuel flow from hot pits	+170	gpm
Rate of fuel burn (single engine idle) while hot refueling at hot pits	-5	gpm
Assumed refuel transit time for fuel trucks	10	minutes
Assumed refill transit time for fuel trucks	5	minutes
Assumed coupling time between fuel trucks and aircraft	3	minutes

Table 2. Fixed parameters. For example, the 'Assumed coupling time between fuel trucks and aircraft' is three minutes for all cases. We hold these parameters steady throughout all of our simulation runs.

3. State Variables

State variables represent the system at a snapshot in time, are dynamic, and typically change frequently during a simulation. For example, the fuel level in each mobile refueling truck depends on its individual activity throughout the day. The status of the truck may also change from available to not available if it runs low on jet fuel and needs refilling.

Table 3 presents our model's state variables. These describe refueling at NAS Oceana using the behavior of aircraft arrivals and the quantity of jet fuel (measured in gallons) required by each aircraft. In the primary stage, fuel is transferred either from refueling trucks to aircraft or from hot pits to aircraft. In the secondary stage, fuel is transferred from refilling stations to refueling trucks (hot pits are considered to have infinite supply). This interaction is mathematically translated to the changing states of aircraft, trucks, hot pits, and refilling stations. The end result is a measure of the system's effectiveness in terms of the time that each aircraft must wait until it is refueled and ultimately departs the system.

State Variable Description	Units
Total number of jet arrivals to the system	jets
Number of refueling trucks available for jet refueling use	trucks
Number of hot pits available for jet refueling use	hot pits
Number of refilling stations available for truck refilling use	refill stations
Number of jets in cold refueling queue	jets
Number of jets in hot refueling queue	jets
Number of refueling trucks delayed in refilling station queue	trucks
Present jet fuel onboard each truck	gallons
Total jet fuel dispensed by each truck	gallons
Total number of jets served by each truck	jets
Total jet fuel dispensed by each hot pit	gallons
Total number of jets served by each hot pit	jets
Total delay in queue for each aircraft	minutes
Total time in system for each aircraft	minutes

Table 3. State variables. Together these represent the minimum traits of the refueling system that broadly capture the behavior of the interactions between jets, trucks, hot pits, and jet fuel.

4. Scheduling Relationships

Scheduling relationships are rules that trigger future events. For example, when a jet finishes refueling, the aircraft queue is checked to see if another jet needs fuel. Future events are processed in the order that they appear on the future event list. Figure 4 describes the logic used to execute the simulation.

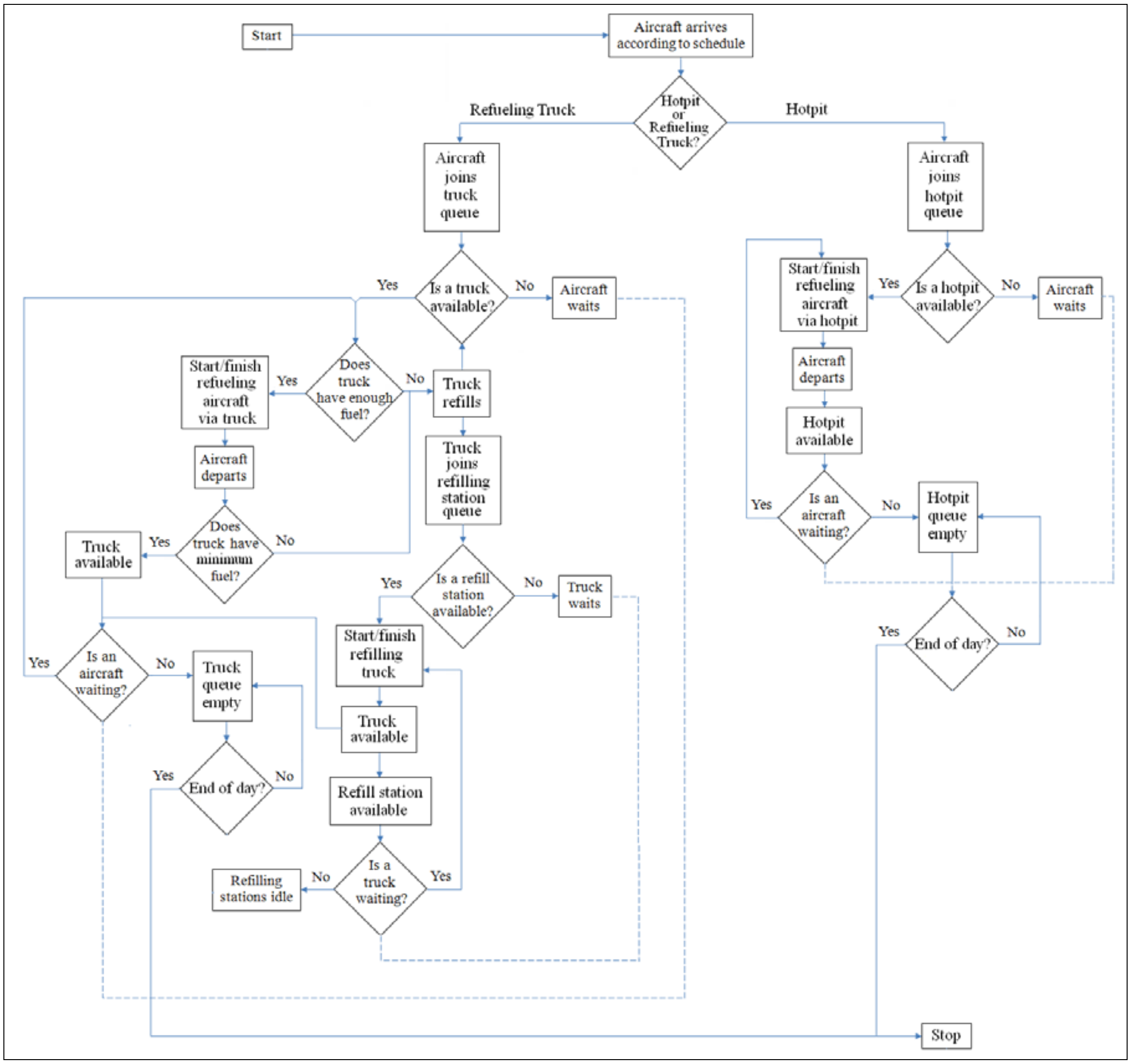


Figure 4. Summary flowchart of interactions between aircraft, refueling trucks, hot pits, and refilling stations. The logic depicted here is the same that entities follow during the course of simulation, with each decision point in the flowchart mapping to a logical test in the computer model.

5. Events

Events are unique, significant activities that take place within a system. Events may cause state variables to change and may trigger other events. In our simulation, aircraft arrivals are events that start the queueing and fueling system in motion.

6. Event Graph

The event graph we use for our model is illustrated in Figure 5. This ties together the basic components of our discrete-event simulation model into a coherent whole.

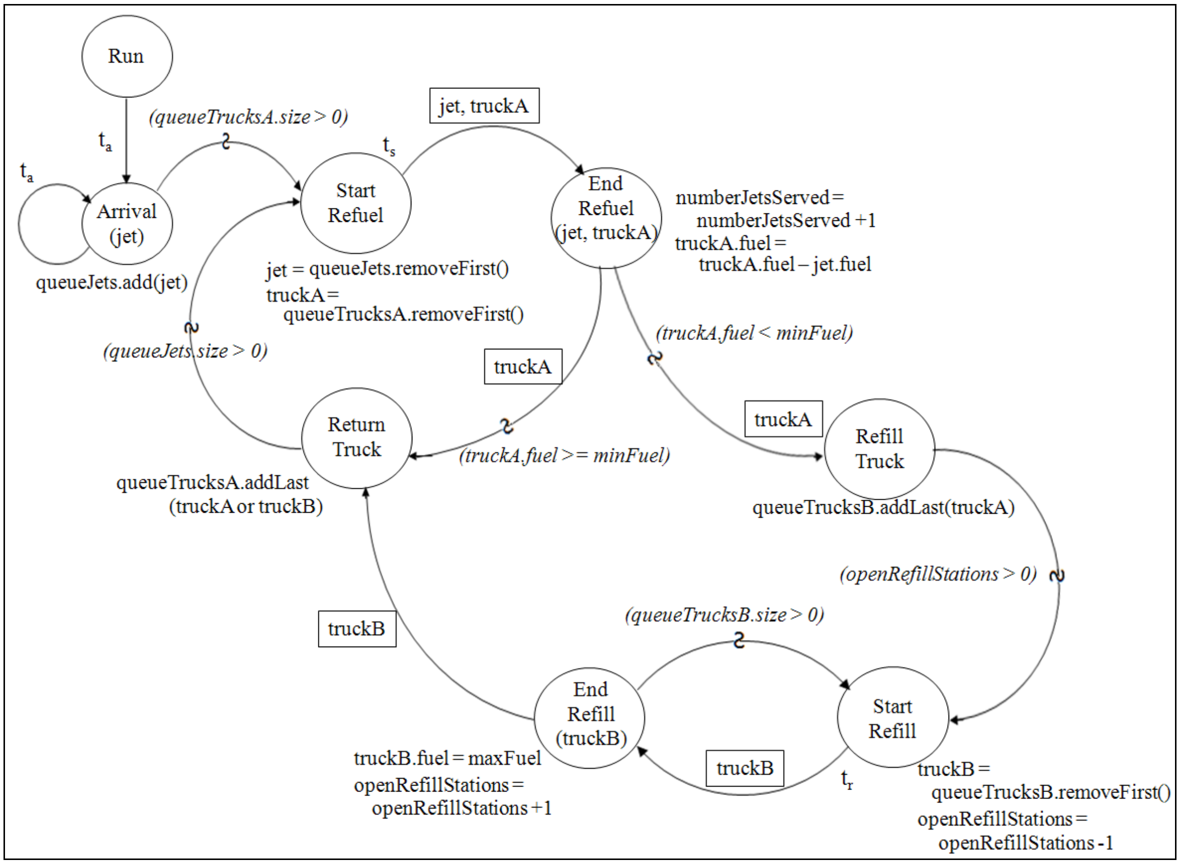


Figure 5. Initial event graph of major elements. Each circular node indicates an event (or a state transition) and each directed edge causes other events to be scheduled. Some directed edges also include time delays and conditional requirements to trigger appropriate responses within the system. Note that this event graph shows only the refueling truck portion of the system; the hot pit portion of the system has a similar structure, except 'hot pit' is substituted for 'truck' and no 'refill' event exists.

F. SIMKIT

We implement our simulation model with Simkit, an open source collection of Java classes (Oracle Corporation, 2012) specifically designed to run DES models.

We use Simkit version 1.3.8 requiring Java development kit (JDK) 1.6 or higher; for details see Buss (2010). We use random numbers created by the Tausworthe class; for details see Law and Kelton (2000).

G. MODEL VERIFICATION

We use the analytic results of the M/M/k queue and M/M/1 queue to verify that our model is coded correctly. The aircraft arrivals in our computer simulation qualify as a counting process. Thus, we are able to compare output from our model with known standard analytic results described by Ross to verify that our computer simulation performs as expected. Specifically, we test Markovian arrivals, together with Markovian service for 100,000 units of simulated time. Figure 6 presents our results. For details on computing the wait times for the M/M/1 queueing model see Heathcote and Winer (1969).

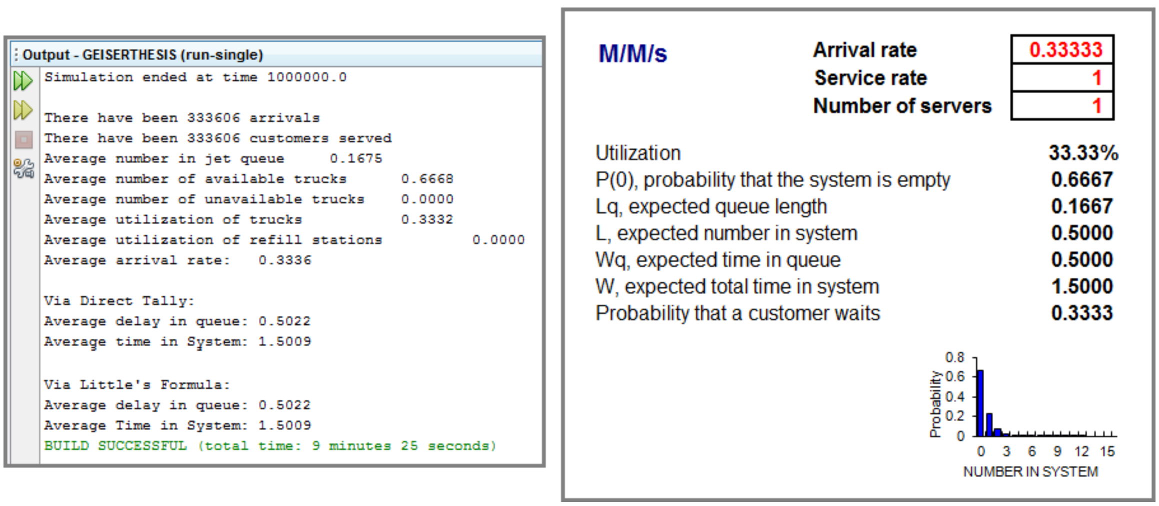


Figure 6. Comparison of our computer simulation model output (left) to known standard analytic results (right). Our computer code appears to function properly and the fundamental queueing model behaves as expected.

Validation requires comparison of simulation results with a large set of airfield data and is beyond the scope of our current effort, but would be promising for follow-on study.

THIS PAGE INTENTIONALLY LEFT BLANK

III. MODELING FUEL DEMAND

A. DATA

Our goal is to understand fuel demands; we use fuel data by calendar day for October 2011 (Figure 7) for analysis. The purpose of this analysis is to get distributional information and use it to represent fuel demands randomly in our simulation model.

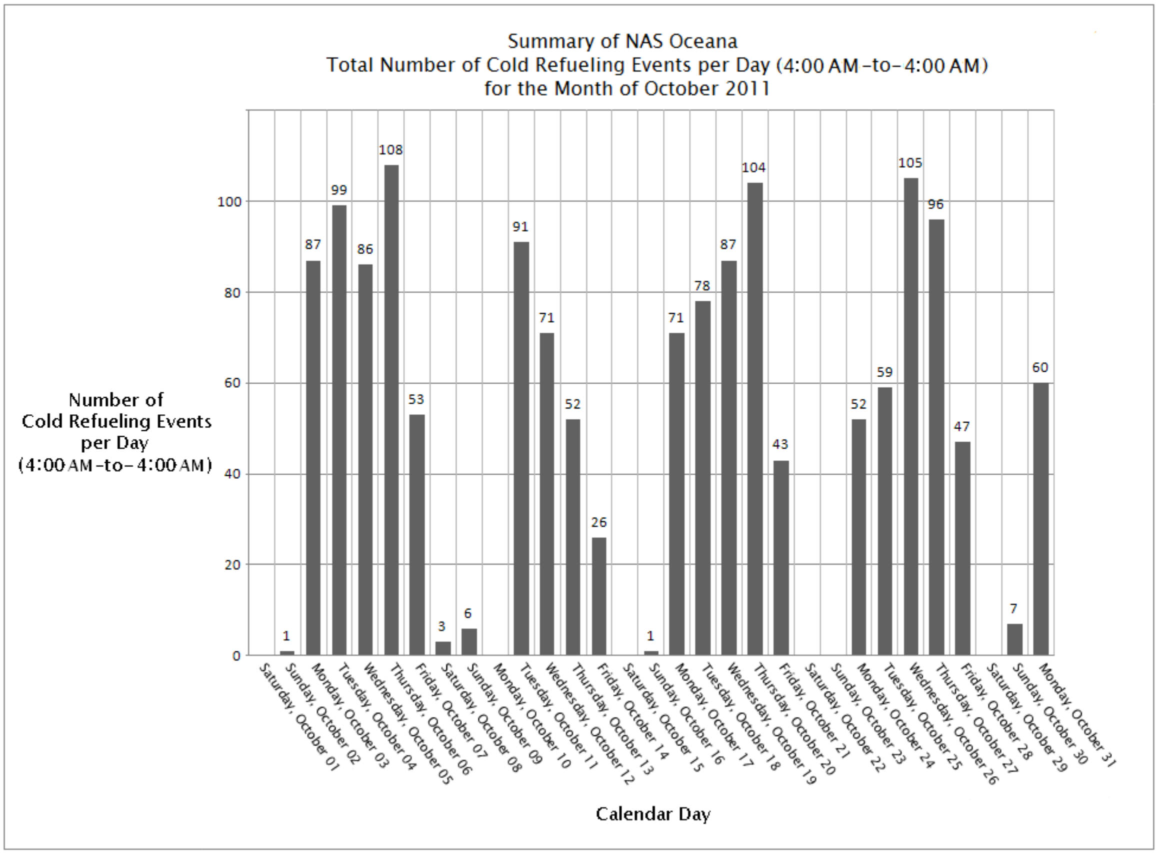


Figure 7. Graph of the total 'cold refueling' events per calendar day (defined as starting and ending at 4:00 AM) during October 2011. This shows a significant day-of-the-week effect, with weekends having substantially less activity than weekdays. Specifically, Tuesday, Wednesday and Thursday are similar, with less activity on Monday and Friday. Note that Monday, October 10 was the Columbus Day holiday and thus saw low activity.

Our dataset (31 days) contains 25 days when at least one aircraft required fuel and six days (four Saturdays, one Sunday, and one Monday) when no fuel activity took place; these days were excluded from our analysis. Of the 25 days when at least one aircraft required fuel, five days experienced ‘low activity’, which operators at NAS Oceana define as fewer than 10 refueling events per 24-hour period. Therefore, we have 20 days of useful data for analysis.

After plotting each day’s data, we note that the system is empty each night at 4:00 AM. The operational experience of the fuel operators confirms this finding. We therefore treat 4:00 AM as a fixed starting and stopping point for each day’s refueling activity. This streamlines our analysis because we need not be concerned with ‘spillover’ work in the form of aircraft remaining in the queue from the previous day; each day is independent. Therefore, we treat our dataset as 20 independent days, vice one sample containing 20 days of data.

We also look at the characteristics of the individual fuel requirements (i.e. the unique amount of fuel required by each aircraft) for the entire month of October.

We observe a total of 1,493 fuel events. Two fuel events exceed the 5,000-gallon maximum capacity of the existing fleet of mobile refueling trucks. We do not discard these points because there are transient aircraft serviced by NAS Oceana that require that much fuel, such as the E-6B Mercury, the C-17 Globemaster, and the C-5 Galaxy. As a modeling consideration, we partition each of these large demands into two smaller demands that arrive near-simultaneously; this maps fuel requirements from the aircraft’s point of view into fuel requirements from the fueling systems’ point of view. This results in 1,495 individual fuel demands on which we base our model.

B. DISTRIBUTION FITTING

The empirical distribution of these individual fuel demands suggests that no single, commonly used parametric distribution adequately describes our data. The primary difficulty lies in the spike near zero (Figure 8). We fit a compound random variable to capture the behavior of the relative sizes of the fuel demands, measured in

gallons of jet fuel. The experience of refueling operators reinforces our observation that 500 gallons and 3,000 gallons are appropriate ‘breakpoints’ to differentiate between small, medium, and large fuel demands. Fitting data with breakpoints introduces additional degrees of freedom; both the parameter estimation (for the individual distributions) as well as finding the breakpoint between neighboring distributions.

Based on our selection of breakpoints, we pass each subgrouping of observed fuel demands into the distribution-fitting platform of JMP statistical software, base version 9.0.1. (SAS Institute Inc., 2012) This software uses second-order information criterion known as Akaike information criterion corrected (AICc) to fit a model with the fewest parameters for a finite sample-size. See Burnham and Anderson (2002) for more information.

To represent the subgroup consisting of 211 small demands, we choose from four viable candidate distributions with comparable measures of relative goodness of fit and number of parameters as follows: eight (Normal 3 Mixture), five (Normal 2 Mixture), and two (Gamma or Weibull). To represent the subgroup consisting of 1,273 medium demands, we choose from five viable candidate distributions with comparable measures of relative goodness of fit and number of parameters as follows: eight (Normal 3 Mixture), five (Normal 2 Mixture), three (Johnson Sl), four (Johnson Su), and two (Weibull). Due to their applicability and simplicity, we select both two-parameter Weibull distributions and confirm with checks on 95% confidence intervals and goodness-of-fit tests that reject the null hypothesis. These results enable us to fit a composite distribution that approximates the observed data behavior.

We approximate the smaller fuel demands (those less than 500 gallons) using a two-parameter Weibull distribution. We approximate mid-sized fuel demands (those between 500 and 3,000 gallons) by a second distinct two-parameter Weibull distribution. The shape fitting properties of the two-parameter Weibull distribution enable us to adequately describe a variety of unique distribution shapes, using a simple form that consists of a shape parameter and a scale parameter (NIST 2012, Devore 2009). Finally, we use a Uniform distribution for large fuel demands (i.e. between 3,000 and 4,500 gallons).

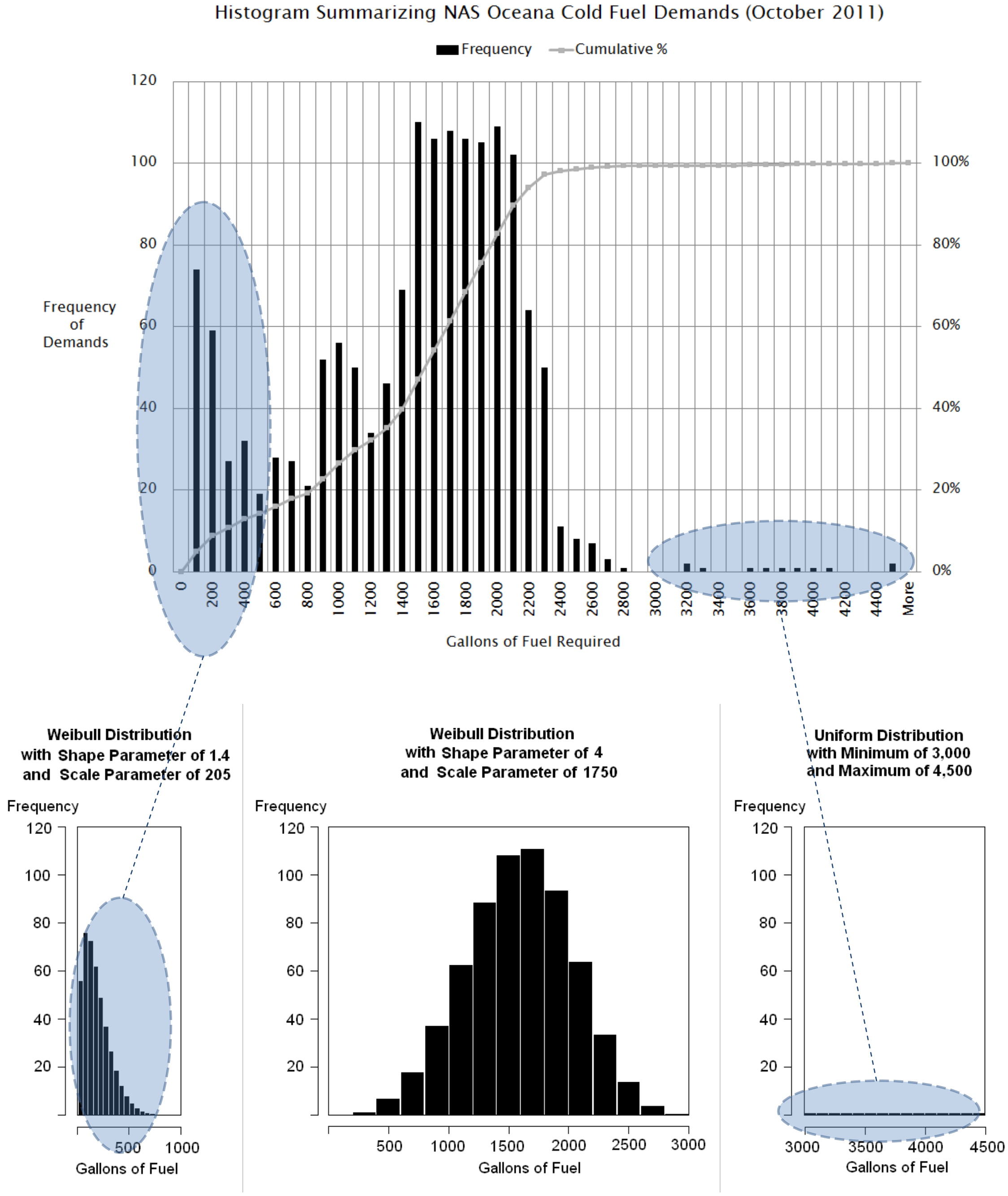


Figure 8. Graph of fuel demands. Empirical distribution is shown at top. The vertical oval highlights 'small' demand signals between 0 and 500 gallons, which we model using a Weibull distribution (shown bottom left in more ideal form). The middle of the distribution between 500 and 3,000 gallons contains the 'medium' demand signals, which we also model using a Weibull distribution (shown bottom center). The horizontal oval from 3,000 to 4,500 gallons contains rare but influential 'large' demand signals, which we model using a Uniform distribution.

The procedure for finding the compound distribution follows: from a truck operator's point of view, when dispatched to refuel an aircraft, he draws a card marked either 'A', 'B', or 'C' from a (biased) deck. Conditional on the card drawn, he then draws from the appropriate distribution described above. We then implement a Bernoulli trial or (three-outcome) coin-flip in our simulation. For example, 1,273 medium fuel demands out of 1,495 total fuel demands is equivalent to an occurrence rate of 0.85. Therefore, we assume in our model that 85% of fuel demands will be between 500 gallons and 3,000 gallons using our second Weibull distribution parameters. We apply the same logic to small fuel demands (211 out of 1,495 total, or 14%) using our first Weibull distribution parameters and to large fuel demands (11 out of 1,495 total, or 1%) using a Uniform distribution.

We choose the Weibull for our simulation model because it empirically resembles our data. As Weibull (1951) himself points out, the distribution has wide applications and "the only practicable way of progressing is to choose a simple function, test it empirically, and stick to it as long as none better has been found."

Devore (2009) describes the probability density function (pdf) of a two-parameter Weibull distribution for random variable *X*, with shape α and scale β, given by:

$$f(x;\ \alpha,\ \beta) = \begin{cases} \dfrac{\alpha}{\beta^{\alpha}}\ x^{\alpha-1} e^{-(x/\beta)^{\alpha}} & x \geq 0 \\ 0 & x < 0 \end{cases}$$

Table 4 summarizes the parameters that we use to construct our composite distribution of fuel demands.

Demand	First Parameter	Second Parameter	Probability	Notation
Small (S) WEIBULL	Shape α = 1.4	Scale β = 205	p_S = 0.14	F_S
Medium (M) WEIBULL	Shape α = 4	Scale β = 1750	p_M = 0.85	F_M
Large (L) UNIFORM	Minimum = 3000	Maximum = 4500	p_L = 0.01	F_L

Table 4. Input parameters that approximate our compound distribution of fuel demands. Together with the formula below, these enable us to produce randomized results.

The cumulative distribution function (cdf) of our compound random variable is given by conditioning. If p_S, p_M, and p_L are the probabilities associated with each type of fuel demand (small, medium, and large), then the overall cdf is given by:

$$F(x) = \Pr\{X \leq x\} = F(X) = p_S F_S + p_M F_M + p_L F_L$$

IV. RESULTS

We are interested in how our computer simulation performs with five factors and multiple levels. Given the speed of our model, running a large number of cases is not a concern, but we wish to interpolate between design points. Specifically, we wish to analyze multiple levels for each of the following factors:

- the percentage of time when hot pits are used;
- the number of refueling trucks in operation;
- the fuel flow rate from each refueling truck;
- the lower limit on the fuel level that is reached before a truck driver refills; and
- the upper limit on the fuel level that each truck carries.

Using a full factorial experiment, we would need at least 162 runs to evaluate the boundary points.

Our goal in the initial experiments is to efficiently assess this sample space and find the relative merits of the five factors mentioned above.

A. EXPERIMENTAL DESIGN

Leveraging the previous work of Cioppa (2002) and Sanchez (2011), we use a nearly orthogonal Latin hypercube (NOLH) design that allows us to perform a fractional factorial experiment with much less computational expense than a full factorial design. We choose the following design points for our selected parameters:

(a) Hot pit policy (between 0% and 30%);

(b) Total number of trucks (between 4 and 20);

(c) Truck fuel flow rate to aircraft (between 70 and 150 gpm);

(d) Minimum fuel level or threshold when each fuel truck driver decides to refill

(0 to 2,000 gallons of jet fuel remaining);

(e) Maximum fuel level that each truck safely carries (4,500 to 5,000 gallons).

We apply our computer simulation using 17 design points to analyze a total of 85 distinct levels across five parameters.

To analyze the behavior of the system with a very large number of mobile refueling trucks, we add one additional design point (‘Case 18’) that consists of 28 total trucks, zero hot pit use, and all other parameters set to the midpoint values of their range. With the 18 design points shown in Table 5, we produce 90,000 data points by using 250 replications across 20 simulation days.

	(a)	(b)	(c)	(d)	(e)
Factor Name	**Hot pit Policy**	**Total Number of Trucks**	**Truck Fuel Flow Rate (gpm)**	**Minimum Truck Fuel Level (gallons)**	**Maximum Truck Fuel Level (gallons)**
Low level	**0.00**	**4**	**70 gpm**	**0 gallons**	**4,500 gallons**
High level	**0.30**	**20**	**150 gpm**	**2,000 gallons**	**5,000 gallons**
CASE 1	0.21	4	85	1,250	4,880
CASE 2	0.08	5	115	1,750	4,840
CASE 3	0.13	6	90	125	4,590
CASE 4	0.19	7	150	625	4,940
CASE 5	0.20	8	140	1,125	4,500
CASE 6	0.30	9	100	1,625	4,530
CASE 7	0.24	10	125	0	4,720
CASE 8	0.04	11	75	500	4,810
CASE 9 *	0.15 *	12 *	110 *	1,000 *	4,750 *
CASE 10	0.26	13	145	1,500	4,690
CASE 11	0.06	14	95	2,000	4,780
CASE 12	0.00	15	120	375	4,970
CASE 13	0.28	16	80	875	5,000
CASE 14	0.11	17	70	1,375	4,560
CASE 15	0.17	18	130	1,875	4,910
CASE 16	0.23	19	105	250	4,660
CASE 17	0.09	20	135	750	4,630
CASE 18	0.00	28	110	1,000	4,750

Table 5. Nearly orthogonal Latin hypercube (NOLH) design. These 18 cases (18 design points) efficiently explore the sample space. Asterisks indicate ‘Case 9’ is the center-point of our five-parameter sample space.

Of particular interest to the operators at NAS Oceana are the potential gains of information-sharing, which we define as knowledge of the fuel requirement before a truck is dispatched to service it. To achieve this, we let the model produce two output streams of results. The first output tells us the mean delay in the aircraft queue when truck drivers know the amount of fuel required by each aircraft prior to an attempted refueling event. The second output tells us the adjusted mean delay in the aircraft queue, or time wasted when a truck driver arrives to refuel an aircraft with insufficient fuel. To do this we add an additional binary parameter for the “value of information”, represented

by a one or a zero. By adding this column to our initial design, we do not change the NOLH design, but our total number of data observations doubles from 90,000 to 180,000.

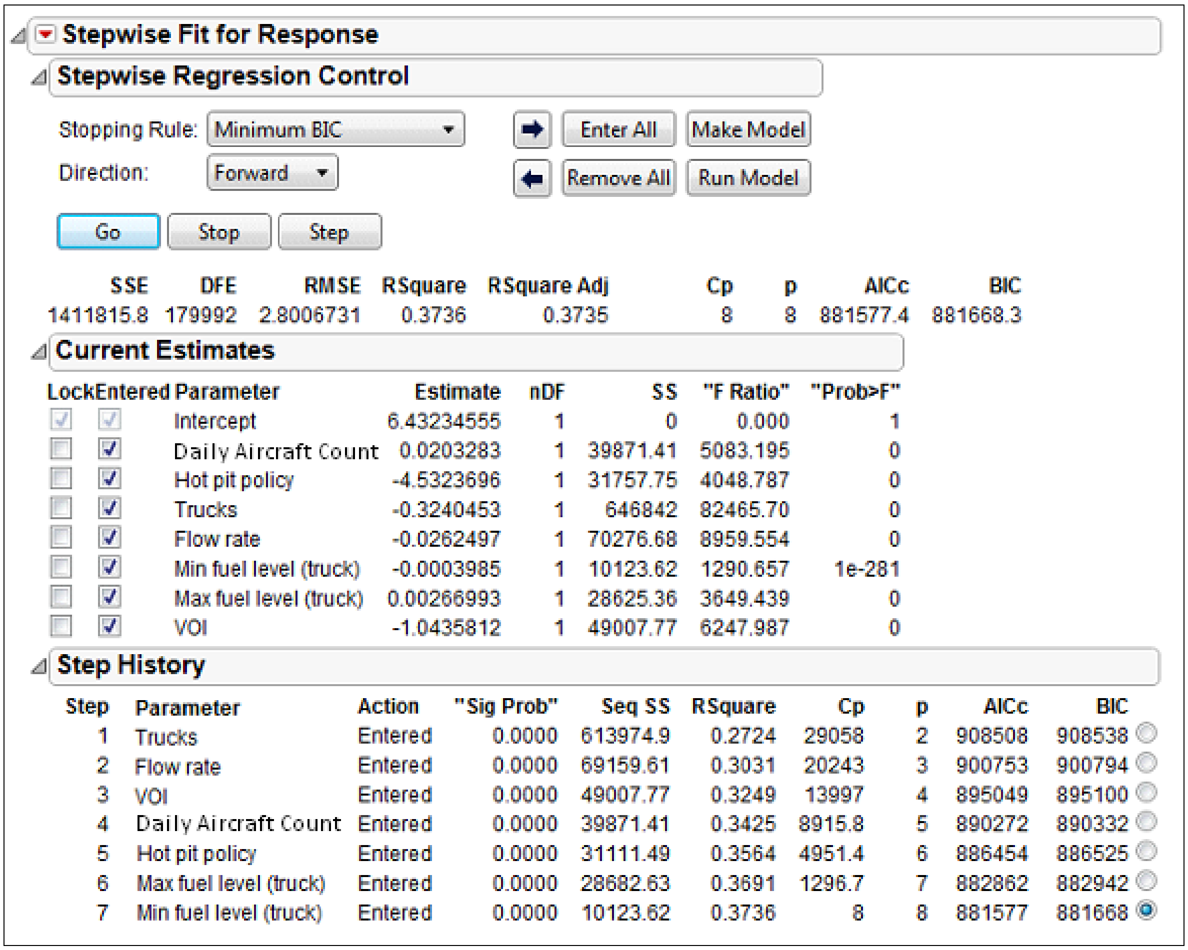
Using this nearly-orthogonal experimental design as our guide, our computer simulation produces the results shown in Table 6.

	Mean Delay in Aircraft Refueling Queue (mins) ***No information-sharing***	**Standard Deviation**	**Mean Delay in Aircraft Refueling Queue (mins)** ***With information-sharing***	**Standard Deviation**
CASE 1	21.21	6.64	20.47	6.55
CASE 2	16.14	3.62	15.86	3.61
CASE 3	17.79	3.22	15.14	3.03
CASE 4	12.92	1.57	11.38	1.35
CASE 5	12.40	1.42	11.30	1.23
CASE 6	10.39	0.49	10.11	0.31
CASE 7	12.71	1.18	10.64	0.86
CASE 8	12.87	1.53	10.96	1.24
CASE 9 *	11.20 *	0.76 *	10.16 *	0.42 *
CASE 10	10.37	0.39	10.01	0.11
CASE 11	10.19	0.40	10.02	0.16
CASE 12	12.17	1.05	10.22	0.59
CASE 13	10.74	0.61	10.02	0.14
CASE 14	10.58	0.55	10.02	0.14
CASE 15	10.16	0.31	10.00	0.04
CASE 16	11.32	0.97	10.05	0.26
CASE 17	11.22	0.80	10.02	0.17
CASE 18	10.80	0.74	10.00	0.06

Table 6. Simulation results from the NOLH design (see Table 5). Note these values represent the mean delay of aircraft prior to fuel truck arrival, rather than the total time in the system. For our analysis, once a fuel truck arrives to fuel an aircraft we stop the timer that measures the system response with respect to each refueling event. Asterisks indicate ‘Case 9’ is the center-point of our sample space. Cases are shown in order from smallest to largest, based on the number of refueling trucks. Notice as number of trucks goes up, mean aircraft delay and standard deviation tend to go down, but not strictly. *Exclusively adding more trucks does not always yield a better result*, due to the combined effects of all parameters. We also find, *in every case, information-sharing lowers mean aircraft delay and standard deviation* (see columns shaded in gray).

B. LINEAR REGRESSION MODEL

Combining results from Table 5 and Table 6, we produce a linear regression and determine the marginal contribution of each factor (Figure 9). All factors turn out to be statistically significant predictors of the mean delay in aircraft refueling queue. The factors in our fitted linear model account for 37% of the variation in the mean delay in queue response variable that results from our NOLH-designed simulation model.



Stepwise Fit for Response

Stepwise Regression Control

Stopping Rule: Minimum BIC

Direction: Forward

Enter All | Make Model | Remove All | Run Model | Go | Stop | Step

SSE	DFE	RMSE	RSquare	RSquare Adj	Cp	p	AICc	BIC
1411815.8	179992	2.8006731	0.3736	0.3735	8	8	881577.4	881668.3

Current Estimates

Parameter	Estimate	nDF	SS	"F Ratio"	"Prob>F"
Intercept	6.43234555	1	0	0.000	1
Daily Aircraft Count	0.0203283	1	39871.41	5083.195	0
Hot pit policy	-4.5323696	1	31757.75	4048.787	0
Trucks	-0.3240453	1	646842	82465.70	0
Flow rate	-0.0262497	1	70276.68	8959.554	0
Min fuel level (truck)	-0.0003985	1	10123.62	1290.657	1e-281
Max fuel level (truck)	0.00266993	1	28625.36	3649.439	0
VOI	-1.0435812	1	49007.77	6247.987	0

Step History

Step	Parameter	Action	"Sig Prob"	Seq SS	RSquare	Cp	p	AICc	BIC
1	Trucks	Entered	0.0000	613974.9	0.2724	29058	2	908508	908538
2	Flow rate	Entered	0.0000	69159.61	0.3031	20243	3	900753	900794
3	VOI	Entered	0.0000	49007.77	0.3249	13997	4	895049	895100
4	Daily Aircraft Count	Entered	0.0000	39871.41	0.3425	8915.8	5	890272	890332
5	Hot pit policy	Entered	0.0000	31111.49	0.3564	4951.4	6	886454	886525
6	Max fuel level (truck)	Entered	0.0000	28682.63	0.3691	1296.7	7	882862	882942
7	Min fuel level (truck)	Entered	0.0000	10123.62	0.3736	8	8	881577	881668

Figure 9. Linear regression analysis results, fit for the total time that aircraft wait as a function of seven main effects. All of the factors that we explored are statistically significant, *with the number of trucks exhibiting the greatest marginal improvement.*

Using these results we now compare factors on a similar scale in order to show the relative tradeoffs between actions that the airfield manager may take, as demonstrated below. Our linear regression model suggests the following:

a) For each additional fuel truck, the mean delay in the aircraft queue is reduced by nearly 20 seconds. We note that this depends on the number of trucks already present in the system.

b) For each additional 10 gpm of fuel flow rate from all trucks, the mean delay in the aircraft queue is reduced by nearly 16 seconds.

c) When information is shared with truck drivers, the mean delay in the aircraft queue is reduced by one full minute.

d) A 10% increase in the use of hot pits reduces the mean delay in the aircraft queue by nearly 30 seconds. By the same logic, a 10% reduction in the use of hot pits increases the mean delay in the aircraft queue by 30 seconds.

e) For each 100-gallon reduction in the maximum amount of fuel that trucks carry (between 5,000 and 4,500 gallons) the mean delay in the aircraft queue is reduced by 16 seconds. One can understand this finding to mean that, above some upper fuel level, each truck driver has adequate fuel to support aircraft refueling, so additional time spent refilling a truck with extra fuel detracts from aircraft refueling in general.

f) For each 500-gallon increase in the minimum fuel level that trucks maintain (between zero and 2,000 gallons) the mean delay in the aircraft queue is reduced by 12 seconds. One can understand this finding to mean that, below some lower fuel level, each idle fuel truck driver could instead be refilling his truck in preparation for the next wave of aircraft.

We conclude from our linear regression model that the ‘best’ actions from a statistical point of view (without regard to costs) are, in order from most significant to least significant:

- Maximize the number of fuel trucks;
- Maximize the fuel flow rate from the trucks;
- Increase the information given to the truck drivers;

- Implement a more liberal hot pit policy;
- Lower the maximum amount of fuel that trucks carry toward 4,500 gallons;
- Increase the minimum amount of fuel that trucks carry toward 1,000 gallons.

THIS PAGE INTENTIONALLY LEFT BLANK

V. CONCLUSIONS AND FUTURE WORK

A. CONCLUSIONS

The objective of this thesis was to identify, analyze and propose a portfolio of solutions to reduce refueling delays at NAS Oceana, by changing policy, and/or materiel resources. The results of this study identify several existing alternatives that should reduce the time that customer aircraft wait for fuel.

We conclude from our analysis that the 'best' actions from a statistical point of view (without regard to costs) are, in order:

1) Increase the number of fuel trucks;
2) Ensure trucks deliver fuel at the maximum allowable rate (i.e. 150 gpm);
3) Ensure that truck drivers have demand information as early as practicable;
4) Consider increased use of hot-pits.

We understand some actions, such as increasing the number of fuel trucks and drivers comes at a monetary cost, while other actions are essentially no-cost and we can broadly compare anticipated effects. Of particular interest is the "Value of Information". Figure 10 describes the effect that this has on system performance. In all cases, the value of information shortens the expected waiting time; in some cases, dramatically.

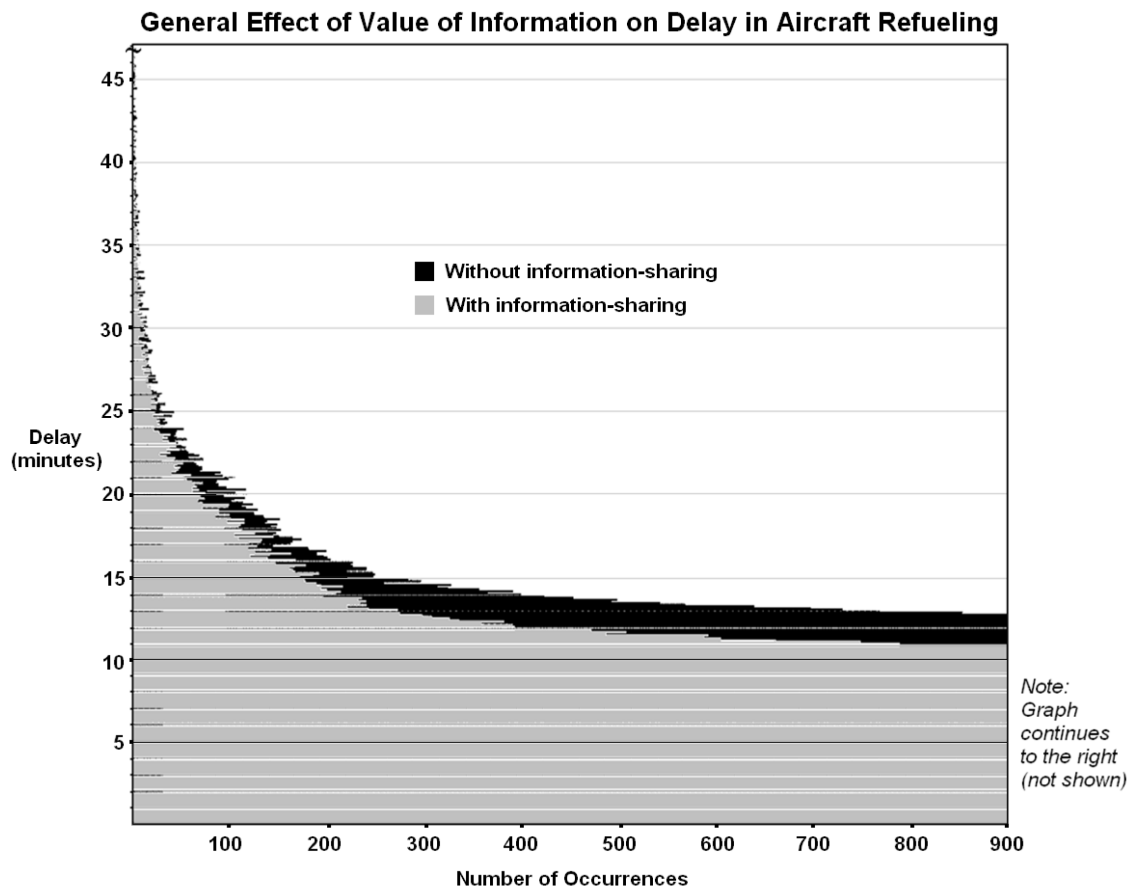


Figure 10. The difference between information-sharing and no information-sharing, regardless of system configuration. Results for all cases are shown here. We see that providing fuel truck drivers in advance with the amount of fuel that each aircraft needs has a limited but noticeable impact on system performance, or delay in the aircraft queue (shown as the vertical axis). This is attributable to reducing the amount of time that fuel trucks expend driving to an aircraft's location instead of refilling. Note that the plot area is slightly truncated at the upper boundary and highly truncated at the right boundary to make the graph viewable.

Incorporating costs, we recommend the leadership at NAS Oceana consider the following actions:

1. Ensure that each mobile refueling truck and each driver is equipped to consistently and safely deliver jet fuel near the practicable limit of 150 gpm. This action should require minimal additional cost.

2. Create a standard operating procedure requiring that a member of either the aircrew or maintenance personnel (as appropriate) provide a quality estimate for the amount of fuel required to the truck dispatcher with adequate lead time, so that each fuel truck driver can anticipate requirements. This action also should not require additional cost.

3. Re-evaluate the current hot pit policy, which limits total hot pit events at 20% or less of all events. Previous analyses considered the costs of fuel burned in the hot pits, but did not consider the potential time savings. Our analysis estimates that increasing hot pit usage by 7% will be operationally equivalent to adding another truck. Ultimately, naval aviation leaders will evaluate the tradeoffs between waiting and fuel burned by idling hot pit customers.

B. FUTURE WORK

Our analysis considered only one month's worth of observations. Additional observations of the aircraft arrival and fuel demand patterns at NAS Oceana would provide a more comprehensive dataset to account for monthly and seasonal trends, if any. This effort would also be needed for model validation.

In order to simplify and run our model, we treat refueling truck transit times as a fixed estimate and constant throughout every case. In reality truck transit times vary depending on the distance that each fuel truck travels. Studying the behavior of the refueling queue with varying truck transit times should provide additional insight into best practices for aircraft refueling.

Evaluating the merits of acquiring some small number of trucks with greater fuel capacity to handle extremely large fuel demands is another area that deserves further exploration.

Finally, understanding the cost of aircraft waiting is an open area for research.

THIS PAGE INTENTIONALLY LEFT BLANK

APPENDIX A. SAMPLE OF FUELS DIVISION OFFICER'S MONTHLY FUELS REPORT FOR OCTOBER 2011

DATE	TIME CALLED IN	TYPE	SQDN	ARRIVAL	START	FINISH	GALLONS	REMARKS	WAIT TIME
2	07:47	C9	56	07:53	07:54	08:13	1669		0:06
3	05:43	S	103	05:53	05:57	06:17	1378		0:10
3	05:43	S	103	06:18	06:20	06:39	1407		0:35
3	05:44	S	103	05:56	05:57	06:17	1584		0:12
3	05:44	S	103	06:18	06:20	06:37	1486		0:34
3	05:44	S	103	05:57	06:05	06:21	1744		0:13
3	05:45	S	11	06:22	06:23	06:41	1759		0:37
3	07:22	T34	SFWSL	07:33	07:33	07:35	57		0:11
3	07:30	R	37	07:39	07:40	07:48	243		0:09
3	07:30	R	37	07:48	07:48	07:53	26		0:18
3	07:30	R	37	07:53	07:53	07:57	31		0:23
3	08:02	S	211	08:10	08:10	08:59	1794		0:08
3	09:10	R	37	09:14	09:14	09:27	1245		0:04
3	09:27	R	131	09:38	09:38	09:41	115		0:11
3	10:32	S	32	10:37	10:37	10:42	239		0:05
3	10:33	S	143	10:43	10:43	10:56	499		0:10
3	10:49	S	105	11:07	11:07	11:30	2203		0:18
3	10:50	S	105	11:06	11:07	11:25	2196		0:16
3	10:50	S	105	11:26	11:26	11:42	1671		0:36
3	11:04	S	32	12:21	12:21	12:38	1963		1:17
3	14:10	S	143	14:17	14:17	14:41	2242		0:07
3	14:11	S	143	14:41	14:41	15:01	2048		0:30
3	14:11	S	143	14:19	14:19	14:42	2022		0:08
3	14:11	S	143	14:42	14:42	15:00	1709		0:31
3	14:12	S	143	14:29	14:29	14:47	1703		0:17
3	14:12	R	37	14:55	14:55	15:12	1502		0:43
3	14:13	R	37	14:23	14:23	14:51	1424		0:10
3	14:22	S	105	15:29	15:29	15:33	2053		1:07
3	14:23	S	105	15:29	15:30	15:49	2518		1:06
3	14:23	S	105	14:58	14:58	15:37	2140		0:35
3	14:23	S	105	15:29	15:30	15:48	2265		1:06
3	14:24	S	32	16:40	16:40	16:53	2116		2:16
3	14:24	S	32	16:04	16:06	16:10	1915		1:40
3	14:25	S	32	15:32	15:51	15:53	1787		1:07
3	14:26	S	136	16:13	16:33	16:34	449		1:47

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF REFERENCES

Abdelghany, K., Abdelghany, A., & Raina, S. (2005). A model for the airlines’ fuel management strategies. *Journal of Air Transport Management, 11*, pp. 199–206.

Abdelghany, K., Shah, S., Raina, S., & Abdelghany, A. (2004). A model for projecting flight delays during irregular operation conditions. *Journal of Air Transport Management*, *10*(6), pp. 385–394.

Burnham, K. P. & Anderson, D. R. (2002). *Model Selection and Multimodel Inference: a Practical Information-theoretic Approach*. Springer: New York.

Buss, A. (2010). "Simkit Home Page." Accessed April 5, 2012 from Naval Postgraduate School website: http://diana.nps.edu/Simkit/

Buss, A., & Halwachs, T. (1999). *Core Validation for Maritime Operations Simulation (MarOpsSim)* (NPS-OR-00-003). Naval Postgraduate School: Monterey, CA.

Cioppa, T. M. (2002). *Efficient Nearly Orthogonal and Space-filling Experimental Designs for High-dimensional Complex Models*. Doctoral dissertation, Naval Postgraduate School, Monterey, CA.

Decker, T. (2011). Private communication, November 9, 2011.

Department of the Navy. (2012). *FY2013 President's Budget*. Accessed March 30, 2012, from Office of the Assistant Secretary of the Navy website: http://www.finance.hq.navy.mil/FMB/13pres/Supp_Book.pdf

Devore, J. L. (2009). *Probability and Statistics for Engineers and the Sciences.* Thomson-Brooks/Cole: Belmont, CA.

Dummar, J. K. (2011). *Improving the Integrated Training Center (ITC) Model to Achieve More Accurate Time to Train Estimates*. M.S. Thesis in Operations Research, Naval Postgraduate School, Monterey, CA.

Government Accountability Office. (2010). *Tactical aircraft: DOD’s ability to meet future requirements is uncertain, with key analyses needed to inform upcoming investment decisions* (Report No. GAO-10-789). Accessed March 30, 2012 from Government Accountability Office website: http://www.gao.gov/new.items/d10789.pdf

Heathcote, C. R. & Winer, P. (1969). An approximation for the moments of waiting times. *Operations Research*, *17*(1), pp. 175–186.

Jacobson, S. H., Hall, S. N., & Swisher, J. R. (2006). Discrete-event simulation of health care systems. *International Series in Operations Research & Management Science*, *91*, pp. 211–252. Springer: New York.

Jun, J. B., Jacobson, S. H., & Swisher, J. R. (1999). Application of discrete-event simulation in health care clinics: a survey. *The Journal of the Operational Research Society, 50*(2), pp. 109–123.

Jung, Y., Hoang, T., Montoya, J., Gupta, G., Malik, W., Tobias, L., & Wang, H. (2011). Performance Evaluation of a Surface Traffic Management Tool for Dallas/Fort Worth International Airport. *Ninth USA/Europe Air Traffic Management Research and Development Seminar*, pp. 1-10. Accessed April 2, 2012 from NASA website: http://www.aviationsystemsdivision.arc.nasa.gov/publications/2011/ATM2011_Jung.pdf

Knight, J. (2011). Private communication, November 14, 2011.

Kumar, A. P. & Kapur, R. (1989). Discrete simulation application - scheduling staff for the emergency room. *Proceedings of the 1989 Winter Simulation Conference,* pp. 1112–1120.

Law, A. M. & Kelton, W. D. (2000). *Simulation Modeling and Analysis*. McGraw-Hill: Boston.

Mustafee, N., Katsaliaki, K., Taylor, S. (2010). Profiling Literature in Healthcare Simulation. *Simulation, 86,* pp. 543–558.

National Aeronautics and Space Administration (NASA). (2011). "Surface Automation." Accessed April 2, 2012 from NASA website: http://www.aviationsystems division.arc.nasa.gov/research/surface/index.shtml

National Institute of Standards and Technology (NIST). (2012). "Families of Distributions." Accessed April 2, 2012 from NIST website: http://www.itl.nist. gov/div898/handbook/eda/section3/eda363.htm

Naval Aviation Enterprise. (2011). *Naval Aviation Enterprise Air Plan #19, August 2011*. Accessed March 30, 2012, from Naval Aviation Enterprise website: http://www.public.navy.mil/airfor/nae/Pages/Air_Plans.aspx

Naval Aviation Enterprise. (2012). *Naval Aviation Vision, January 2012*. Accessed March 30, 2012, from Naval Aviation Enterprise website: http://www.cnaf.navy.mil/nae/

Naval Supply Systems Command (NAVSUP) Fleet Logistics Center, Norfolk. (2012). *Supply Chest, 63*(1). Accessed March 30, 2012 from NAVSUP website: https://www.navsup.navy.mil/navsup/ourteam/navsupgls/navsupnavn/news/supply_chest_archives/2012/Jan.%2017%20Supply%20Chest.pdf

Office of the Chief of Naval Operations. (2009). OPNAVINST 3710.7U (series), NATOPS General Flight and Operating Instructions, Chapter 4.

Oracle Corporation. (2012). "Java SE Downloads." Accessed April 5, 2012 from Oracle website: http://www.oracle.com/technetwork/java/javase/downloads/index.html

Pidd, M. (1992). *Computer Simulation in Management Science*. Wiley: New York.

Pidd, M. (1994). An introduction to computer simulation. *Proceedings of the 1994 Winter Simulation Conference,* pp. 7–14.

Pitfield, D. E., Brooke, A. S., & Jerrard, E. A. (1998). A Monte Carlo simulation of potentially conflicting ground movements at a new international airport. *Journal of Air Transport Management, 4*(1), pp. 3–9.

Pitfield, D. E. & Jerrard, E. A. (1999). Monte Carlo comes to Rome: a note on the estimation of unconstrained runway capacity at Rome Fiumucino International Airport. *Journal of Air Transport Management*, *5*, pp. 185–192.

Quinn, C. & Zelenka, R. E. (1998). ATC / Air Carrier Collaborative Arrival Planning. *Second USA/Europe Air Traffic Management Research and Development Seminar*, pp. 1-11. Accessed April 2, 2012 from NASA website: http://www.aviationsystemsdivision.arc.nasa.gov/publications/terminal/cap/

Ross, S. M. (2010). *Introduction to Probability Models*. Elsevier Science: Amsterdam.

Sanchez, S. M. (2011). NOLHdesigns spreadsheet. Accessed April 2, 2012 from SEED Center for Data Farming website: http://harvest.nps.edu/

Sargent, R. G. (1988). Event graph modeling for simulation with an application to flexible manufacturing systems. *Management Science*, *34*(10), pp. 1231–1251.

SAS Institute Inc. (2012). "JMP Software Updates." Accessed April 5, 2012 from JMP website: http://www.jmp.com/support/downloads/jmp_software_updates.shtml

Schruben, L. (1987). A "disposable" graphical event synthesizer for teaching simulation model building. *Proceedings of the 1987 Winter Simulation Conference*, pp. 72–76.

Strike Fighter Squadron One Zero Six (VFA-106). (2012). STRKFITRON106INST 5400.1L (series), Squadron Organization and Regulations Manual (SORM). Accessed March 30, 2012 from VFA-106 website: https://www.portal.navy.mil/comnavairfor/CSFWL/VFA106/50005999/5400.1L%20Squadron%20Organization%20and%20Regulations%20Manual%20(SORM).pdf

Stroup, J. S. & Wollmer, R. D. (1992). A fuel management model for the airline industry. *Operations Research, 40*(2), pp. 229–237.

Swain, J. J. (2011). Software survey: simulation—back to the future. *Operations Research Management Science Today*, *38*(5).

Time and Date AS. (2012). “Sunrise and sunset in Norfolk, VA.” Accessed April 5, 2012 from Time and Date AS website: http://timeanddate.com/s/281s

Weibull, W. (1951). A statistical distribution function of wide applicability. *Journal of Applied Mechanics*, *18,* pp. 293–297.

INITIAL DISTRIBUTION LIST

1. Defense Technical Information Center
   Ft. Belvoir, Virginia

2. Dudley Knox Library
   Naval Postgraduate School
   Monterey, California

3. CDR Harrison Schramm
   Naval Postgraduate School, Operations Research Department
   Monterey, California

4. Professor Gerald Brown
   Naval Postgraduate School, Operations Research Department
   Monterey, California

5. CDR Trent Kalp
   Regional Supply Office Oceana
   Virginia Beach, Virginia

6. LT Jeff Knight
   Regional Supply Office Oceana, Fuels Division
   Virginia Beach, Virginia

7. LCDR Matt Geiser
   Commander, Logistics Forces (COMLOGFORNAVCENT)
   Manama, Bahrain